

# Requirement Analysis for an Intelligent Warning System to Alarm the Rapid Response Team Prior to Patient Deterioration

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**Abstract.** The early warning system alarms the rapid response team (RRT) for clinical deterioration monitoring and prediction. Available systems do not perform well to decrease the number of ICU transfers or death. This study aimed to address the requirement of an intelligent warning system for timely and accurate RRT activation. Methodology: A literature review was conducted in scientific databases to extract data. Then, a questionnaire was developed for experts' views collection (N=12). The collected data were analyzed using the Content Validity Ratio (CVR). According to the Lawshe table for the corresponding number of experts, the cut-off=0.56 for items to be accepted/rejected was considered. A schematic structure was suggested. Findings: The analysis of the extracted papers (N=24) and qualitative analysis addressed 44 requirements in the frame of five involved sub-systems, including a patient monitoring system, electronic health record, clinical decision support system, remote monitoring patient, and dashboard & registries. They were confirmed by meeting the least cut-off value (CVR= 0.86). Conclusion: An integrated approach and technologies of IoT, deep and machine learning techniques, big data, advanced databases, and standards to create an intelligent EWS are required.

**Keywords.** Clinical deterioration, warning system, artificial intelligence, monitoring

## 1. Introduction

Clinical deterioration (CD) in hospital wards usually is considered as a prior event of patient transfer to intensive care unit (ICU), or death(1). Correctly and timely identification of patients at risk of clinical deterioration during their hospitalization is an important concern and has been an upsurge of interest to triage them well-timed and properly by the Rapid Response Team (RRT) (2). Current Early Warning Systems (EWS) need improvements. Beth Smith et al. stated the need for system improvement

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and automation to reduce the remaining uncertainty in applying the current EWS for cardiac arrest and death (3). Romero-Brufau et al. stated that the dynamic entities of CD (4) yield a high number of false alerts and alert fatigue (5). Emerging technologies may improve EWS for advanced automated real-time monitoring, timely diagnosis, accurately warning at CD, and precise prediction of adverse events as early as possible (6, 7). Further study is required for advanced EWS design and development (8). This study aimed to suggest a new method featured with intelligence functions, comprehensively integrated sub-systems to predict CD and activate the RRT timely and accurately.

## **2. Material and Methods**

### *2.1. Data collection*

A cross-sectional, mixed-method study was aimed to determine the requirements for an intelligent integrated system to alarm RRT for CD in a clinical setting. The primary requirements for this system were gathered from a review of available systems, their lack and suggestions for improvement. The search strategy was ('clinical deterioration' OR 'patient deterioration' OR 'deterioration' OR 'pulmonary failure' OR 'Heart failure') AND ('system' OR 'early warning system' OR 'prediction' OR 'model' OR 'sensor' OR 'monitoring system' OR 'clinical decision support system' OR 'decision making' OR 'artificial intelligent'). The literature review step was done according to PRISMA (9) as it is composed of the preferred reporting items for systematic reviews emphasized by Cochrane authors. The search was conducted in October 2021 in three databases: PubMed, Scopus, and Web of Science; after removing the repeated records, finally, 24 records were included (Fig.1). By reviewing the items in the level of full text, the data were categorized based on system type, their lacks, and suggestions for improvement. The suggestions were defined in the frame of a questionnaire to be reviewed by Medical Informatics specialists with medical (N=2), and engineering (N=2) backgrounds. After confirming the designed questionnaire, an online data collection tool was created and the link was shared via Telegram messenger with a group of Medical Informatics experts (N=6 with engineering, and N=6 with medical or nursing background) using accessible sampling method. The online questionnaire for data collection encompassed suggested requirements in five main sections on one side, and four scales of the MoSCoW rating method including "Must have", "Should have", "Could have", and "Won't have" (10) on the other side. This method provides the opportunity for respondents to express their views for each item via four options, differing from 'must' to 'would' which are the scales from most confident to the most arbitrary choices respectively. For analysis, content validity ratio (CVR) was applied as it determines the degree to which the items on the list represent the entire content domain (11). According to the Lawshe table, it is easy to calculate and interpret based on the number of experts on one hand and the essential agreement for the item on the other hand. CVR and Lawshe are two related concepts and are used together(12).

### *2.2. Data analysis*

To identify the most valid requirements of the proposed system for CD prediction and RRT activation, the collected data were analyzed using (CVR):

$$CVR = \frac{N_e - \frac{N}{2}}{\frac{N}{2}} \quad (1)$$

Where N is the total number of experts (N=12) and Ne refers to the count of experts that chose “Must have” or “Should have” to consider the features as essential requirements. The threshold was considered based on the nearest original thresholds introduced by Lawshe(12); it was set at 0.56 as there were 12 experts in the study.

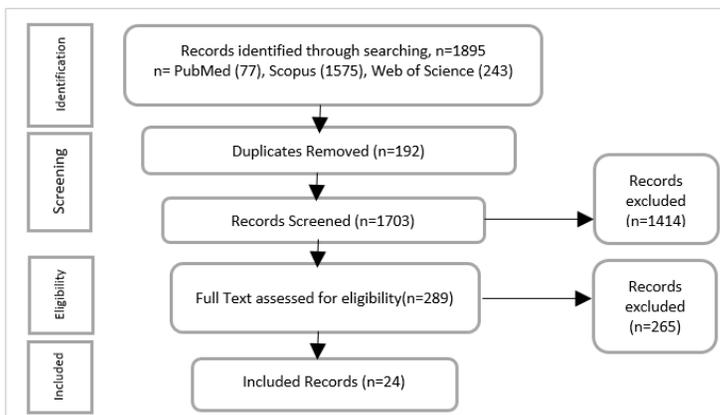


Figure 1. The PRISMA process of the literature review step of the methodology.

### 3. Results

#### 3.1. Experts' Characteristics

The questionnaire was completed by 12 experts (female=4, male=8). 6 were Medical Informatics experts with clinical backgrounds and 6 were Medical Informatics with an engineering backgrounds. All of them have been working as experts in medical universities affiliated with the Iranian Ministry of Health and Medical Education. Their mean of work experience by year has been 5.6. They were working mostly in Tehran, Mashhad, and Kerman in the capital, north-east and north-south of Iran respectively.

#### 3.2. Requirement Prioritization

The responses to the four-choice questions based on the MoSCoW and the CVR for each item was calculated and in Table 1 presented. Based on CVR values for each item (threshold (0.56)), 44 requirements with CVR>0.83 at least, were considered as essential requirements, categorized into 5 main sub-systems.

Table 1. Reviewed Subsystems and their required features approved by experts based on CVR values, (N=12).

Sub-Systems	Related Item and Definition	Respondents Results				Total CVR
		Must	Should	Could	Would	
	To collect real-time vital signs data	12	0	0	0	1.00

Patient	To pool data on inpatient cases	10	1	1	0	0.91	
	Cloud Data fusion development	11	0	1	0	0.91	
Monitoring	Automated data collection using IoT*	10	1	1	0	0.91	
	Vital sign data integration with EHR	9	2	1	0	0.91	
System	Data connection with a warehouse of EHR	8	2	1	1	0.83	
	Standards usage for data interoperability	10	1	0	1	0.91	
	Metadata development and accessibility	12	0	0	0	1.00	
	Standardized storage for big data	10	0	1	1	0.83	
	Automated data quality checking	11	0	1	0	0.91	
	Personal health records development	12	0	0	0	1.00	
Electronic	Interoperability with other EMR/EHR	11	1	0	0	1.00	
Health	To collect necessary clinical notes	8	2	1	1	0.83	
Record	To have minimum data set for CD	10	0	1	1	0.83	
	To collect necessary laboratory data	11	1	0	0	0.91	
(EHR)	Clinical notes convert into structured data using NPL	8	1	2	1	0.75	
	Voice recognition option for data entry	8	2	2	0	0.83	
	Data exchange with other clinics	12	0	0	0	1.00	
	Big data development and definition	10	1	1	0	0.91	
	Automated data cleaning	9	2	1	1	0.91	
	Data quality approval and improvement	10	2	0	0	1.00	
	Dynamic update standardized databases	12	0	0	0	1.00	
	Clinical Decision Support System	Calculate survival to discharge rate	9	2	1	0	0.91
		Using real-time vital sign index, integrated with clinical and demographical, laboratory data	12	0	0	0	1.00
		To use DL** and ML*** methods	12	0	0	0	1.00
Predict pre-event of CD such as heart failure		12	0	0	0	1.00	
Predict length of stay in ICU, ward, hospital		10	2	0	0	1.00	
To update the model output dynamically		9	1	2	0	0.83	
To sync the model output to the KB****		12	0	0	0	1.00	
Notify RRT by alarm based on risk level		12	0	0	0	1.00	
Remote Monitoring and Telecare System	Mobile app development for remote monitoring	10	1	1	0	0.91	
	App integration with other systems	12	0	0	0	1.00	
	Tele consults	11	1	0	0	1.00	
	Trend analysis of patient status	9	1	0	1	0.83	
	System security and data privacy	12	0	0	0	1.00	
Interoperability and data exchange	Interoperability and data exchange	11	1	0	0	1.00	
	System alarm, notify and reminding	12	0	0	0	1.00	
Dashboard	Data analysis and visualization	10	1	1	0	0.91	
	Minimum data set description	9	1	1	0	0.83	
And Registry System	Multicenter integration	10	1	1	0	0.91	
	Dashboard data update	12	0	0	0	1.00	
Performance monitoring	Performance monitoring	10	1	1	0	0.91	
	Output creation and sharing	9	1	1	1	0.83	
	Security setting and data protection	12	0	0	0	1.00	

IOT\*: Internet of Things, DL\*\*: Deep Learning, ML\*\*\*: Machine learning, KB\*\*\*\*: Knowledge Base

#### 4. Discussion

Current tools for RRT activation due to CD detection focus mainly on routinely measuring patients' vital signs during hospitalization. The data is sometimes manually collected, and stored in spreadsheets that are discarded after discharge. In other cases, tablets, personal digital assistants (PDA), or EHR storage are applied (1). Biosign which is a system working based on vital sign monitoring for CD detection is another choice that has limitations (2). Early Warning Scores (EWS) have limitations of not conveniently being used in practice (13) and the problem of nurse acceptance and adherence (14, 15). Although the CD prediction methods using machine learning

algorithms outperformed the EWS in an academic setting, they were poor to respond acute clinical changes in real clinical status (1); that is, these systems resulted in low certainly evidence indicating little or no difference in-hospital mortality, unplanned ICU admission, length of hospital stay or adverse event (8). However, more advanced outputs from techniques such as deep learning methods (16) might be due to sophisticated feature engineering (5), and more clinical variables application besides vital signs including laboratory results and clinical data (17). Having applied the five sub-systems presented in table 1, enhanced with new technologies confirmed by experts in a comprehensive view may offer a reliable solution to decrease the adverse outcome of CD in a clinical setting. Patterson et al. (2019) systematically reviewed 42 integrated EHR with other systems in an emergency department and concluded that they improve patient safety via standardized data collection, more knowledge obtained from a rich data source such as electronic patient records, and continuous risk of bias estimation (18). As Figure 2 presents, the collected patients' data including vital signs and electronic patient records can simultaneously create a strong data storage and backbone for the CD prediction. The integrated system may benefit the subsystems' potential capabilities to overcome the current systems' limitations. It is composed of improved data collection using IoT, data integration with EHR, stronger standardized databases, and improved output sharing via timely and accurate notifications for RRT.

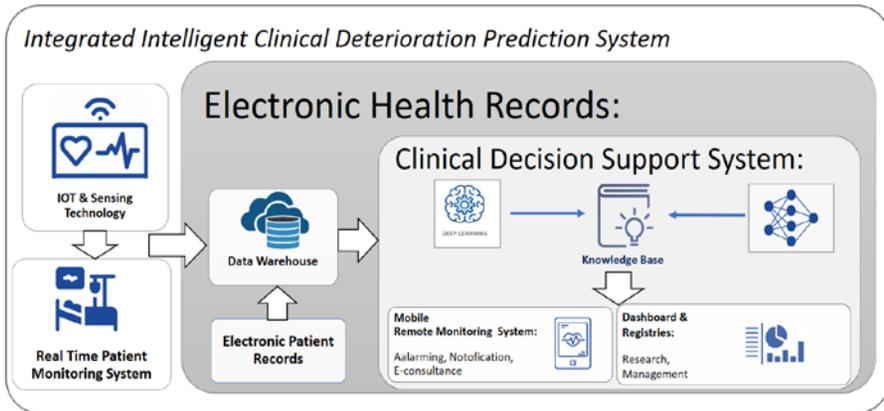


Figure 2. The schematic structure of the proposed system with five integrated sub-systems

Creating such a comprehensive system with intelligent functionality requires a multidisciplinary team working with financial, scientific, and administrative support. It is expected to decrease uncertainty in applying EWS and deduct the false alerts and alert fatigue through enriched databases supported by IoT; the system benefits from the high level of artificial intelligent algorithm to analyze collected data and feed the knowledge-based of the CDSS. More real-time data collection results in a higher level of validated knowledge. This knowledge may strongly support the decision-makers in the case of CD prediction. The communication with care providers is improved due to available mobile apps and this causes timely data communication and interoperability. No information would be lost due to the access to the registry and the visual information will be presented through dashboards to stakeholders particularly policymakers for more optimized decision making. The dynamic entity of CD and the momentary progress of its process require such a system to prevent patient death, reduced the length of hospital stay, and fewer referrals to ICU. Furthermore, this system may support evidence-based medicine

by providing CDSS for care providers leading to fewer false-positive cases and reducing alert fatigue. The comprehensive view of this integrated system, which benefited from most of the available technologies, is the innovation of this study.

Although all system features come from the state of the art with significant benefits and advantages, the required hardware software requires time to be developed and tested in the future. The system may be implemented expensively and require enhanced coordination and support from various sources. Another limitation is system adaptation and preparation to be accepted which cause further costs for establishment. Further study may focus on system design to pass from requirement analysis into more practically system design with architectural suggestions.

It is concluded that investment is required to push the theoretical platform and design to practical steps which may return the cost by health-related awards such as fewer patients death, ICU stay, and readmission in the future. It may improve the level of care and results in more satisfaction for nurses via less workload due to automation, and also for patients by their quality of life improvement.

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